Can Yalçın

Leveraging Advanced Machine Learning to Predict Climate Change:

A Practical Guide for ClimateWins

Objective & Overview

Predict weather patterns and identify Europe's safest regions from extreme weather.

Detecting New Patterns:

Analyze weather changes over the last 60 years to uncover new patterns.

Identifying Anomalies:

Determine weather patterns that deviate from regional norms in Europe and assess if unusual weather events are on the rise.

Forecasting and Safety:

Generate forecasts for weather conditions over the next 25 to 50 years based on current trends, and identify the safest regions in Europe for people to live during this period.

Machine Learning Tools

Algorithm Overview

Random Forests

- **What They Do:** Combines multiple decision trees to improve predictive accuracy.
- **Application:** Feature importance analysis and risk assessments for identifying safe regions.

CNN & RNN (Convolutional Neural Networks & Recurrent Neural Networks)

- **What They Do:** CNNs detect spatial patterns.
- RNNs capture temporal dependencies in sequential data.
- **Application:** Identify deviations in weather patterns and forecast future conditions.

GAN (Generative Adversarial Network)

- **What They Do:** Create synthetic data by pitting two neural networks against each other.
- **Application:** Simulate future weather scenarios to predict potential climate change.

Analyzing Weather Pattern Deviations

Concept:

- Examine and identify significant deviations in weather patterns across Europe from historical regional norms to understand the potential impacts of climate change.

Data Collection:

- Utilize historical weather data from various European regions spanning the last 100 years.

Convolutional Neural Networks (CNNs) & Generative Adversarial Networks (GANs):

  - Analyze spatial data to detect patterns and anomalies across different regions.
  - Generate synthetic weather data and compare it to historical data to identify anomalies.

K-Nearest Neighbors (KNN) & Decision Trees:

- Employ for initial anomaly detection.
- Identify and interpret simpler relationships within the weather data.

Cnn Model
In Practice

Pred	BELGRADE	DEBILT	DUSSELDORF	KASSEL	MAASTRICHT	OSLO	SONNBLICK
True							
BASEL	2265	249	7	30	350	63	6
BELGRADE	885	0	0	0	0	0	0
BUDAPEST	164	0	0	0	0	0	0
DEBILT	64	0	0	0	0	0	0
DUSSELDORF	36	0	0	0	0	0	0
HEATHROW	68	0	0	0	0	0	0
KASSEL	10	0	0	0	0	0	0
LJUBLJANA	47	0	0	0	0	0	0
MAASTRICHT	5	0	0	0	0	0	0
MADRID	311	8	0	2	5	0	0
MUNCHENB	7	0	0	0	0	0	0
OSLO	5	0	0	0	0	0	0
STOCKHOLM	1	0	0	0	0	0	0
VALENTIA	2	0	0	0	0	0	0

Confusion Matrix from CNN Model for Weather Condition Classification

Accuracy Rate 19%

Analyzing Weather Pattern Deviations

- **Concept:**
  - Investigate historical data to identify whether the frequency and intensity of unusual weather patterns are increasing, indicating potential shifts in climate behavior.
- **Data Collection:**
  - Gather historical time-series data on weather anomalies.
- **Algorithms:**
  - Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) & Random Forests:
    - Examine sequential data to identify trends and patterns over time.
    - Evaluate feature importance and detect trends in weather data.
  - **Artificial Neural Networks (ANNs) & K-Nearest Neighbors (KNN):**
    - Serve as supplementary models to capture non-linear relationships and enhance trend analysis.

Rnn Model
In Practice

Pred True	BASEL	HEATHROW	MADRID
BASEL	2975	2	5
BELGRADE	868	0	0
BUDAPEST	150	1	0
DEBILT	67	0	0
DUSSELDORF	18	0	0
HEATHROW	80	0	0
KASSEL	8	0	0
LJUBLJANA	39	0	0
MAASTRICHT	6	0	0
MADRID	347	0	4
MUNCHENB	11	0	0
OSLO	3	0	0
STOCKHOLM	3	0	0
VALENTIA	3	0	0

- **Confusion Matrix from RNN Model for Weather Condition Classification Accuracy rate 12%**

Projecting Future Climate **Scenarios and Safe Regions**

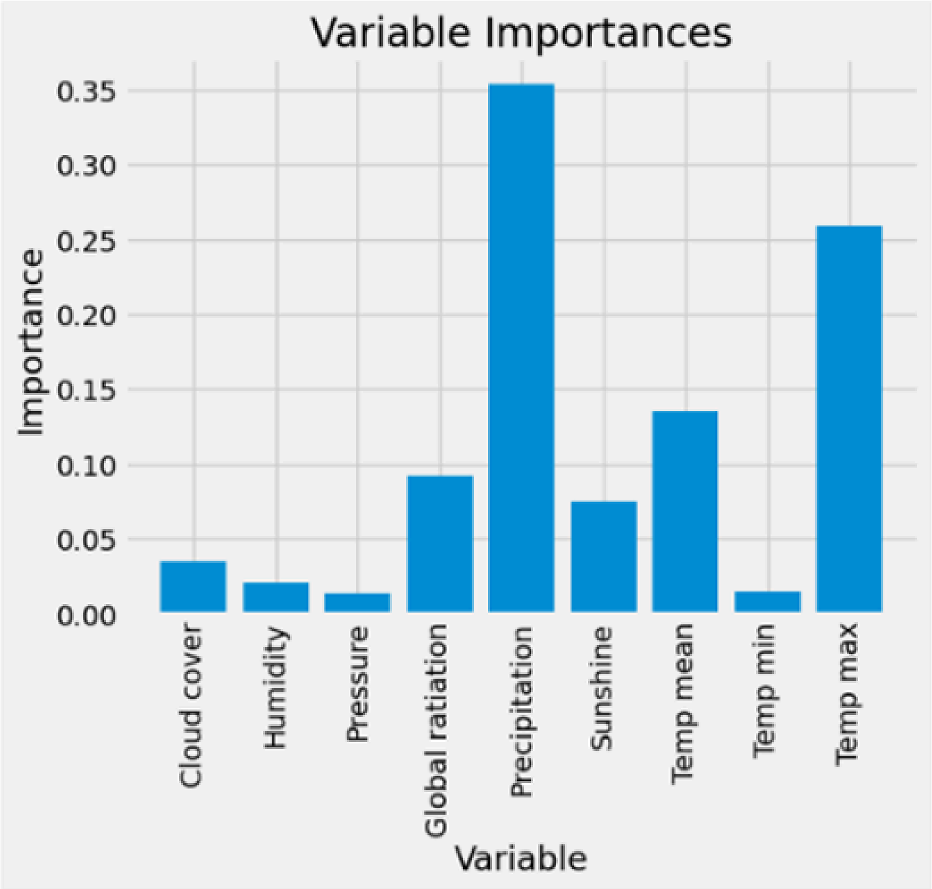
Concept:

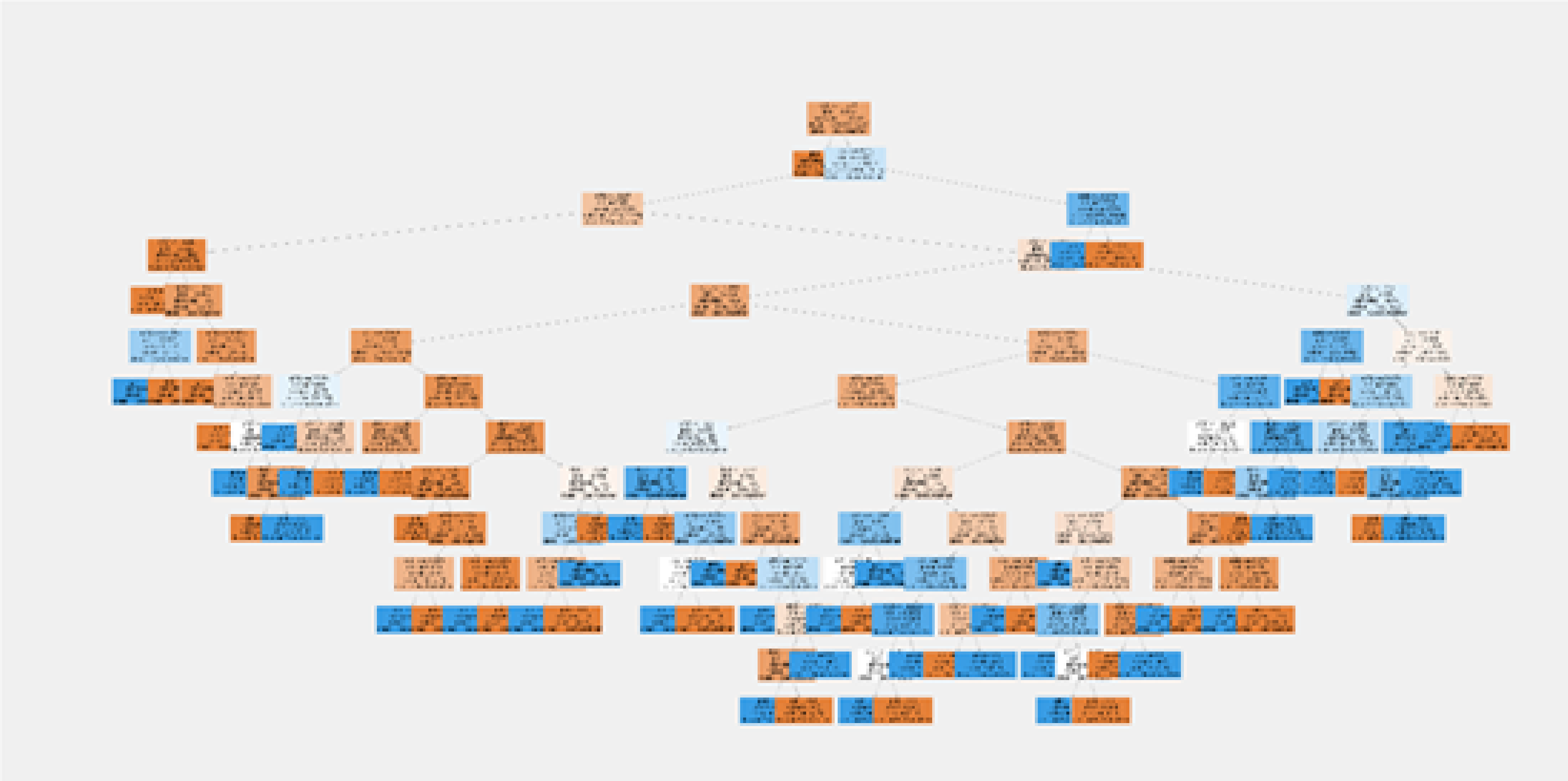
- Generate weather scenarios for the next 25 to 50 years and identify the safest regions in Europe based on these projections.

- **Data Collection:**
  - Historical time-series data on weather anomalies.

- **Algorithms:**
  - **Random Forests & GANs:**
    - Assess risks, predict weather conditions, and evaluate regional safety.
    - Simulate multiple future climate scenarios.
  - **Decision Trees & KNN:**
    - Use for risk categorization and supplementary analysis.
  - **CNN & RNN:**
    - Perform spatial analysis and pattern recognition.

Rnn Model
In Practice





Display a plot showing the significance of various features in the Random Forest model applied to Dusseldorfs weather data. Precipitation and Temp Max have the most influence on the model.

Objective: Utilize Random Forest to classify weather data points from Dusseldorfs weather station into pleasant and unpleasant categories.
Dusseldorf
Accuracy 99%

Results

Low Accuracy in Weather Pattern: The CNNs achieved a 19% accuracy rate in classifying weather conditions. Suggestions for better results :

01

Data Augmentation: Enhance data variety with techniques like rotation and scaling.

02

Hyperparameter Tuning: Optimize layers, kernel sizes, and learning rates.

03

Advanced Architectures: Explore models like ResNet or DenseNet.

04

Feature Engineering: Add relevant features or domain-specific knowledge.

05

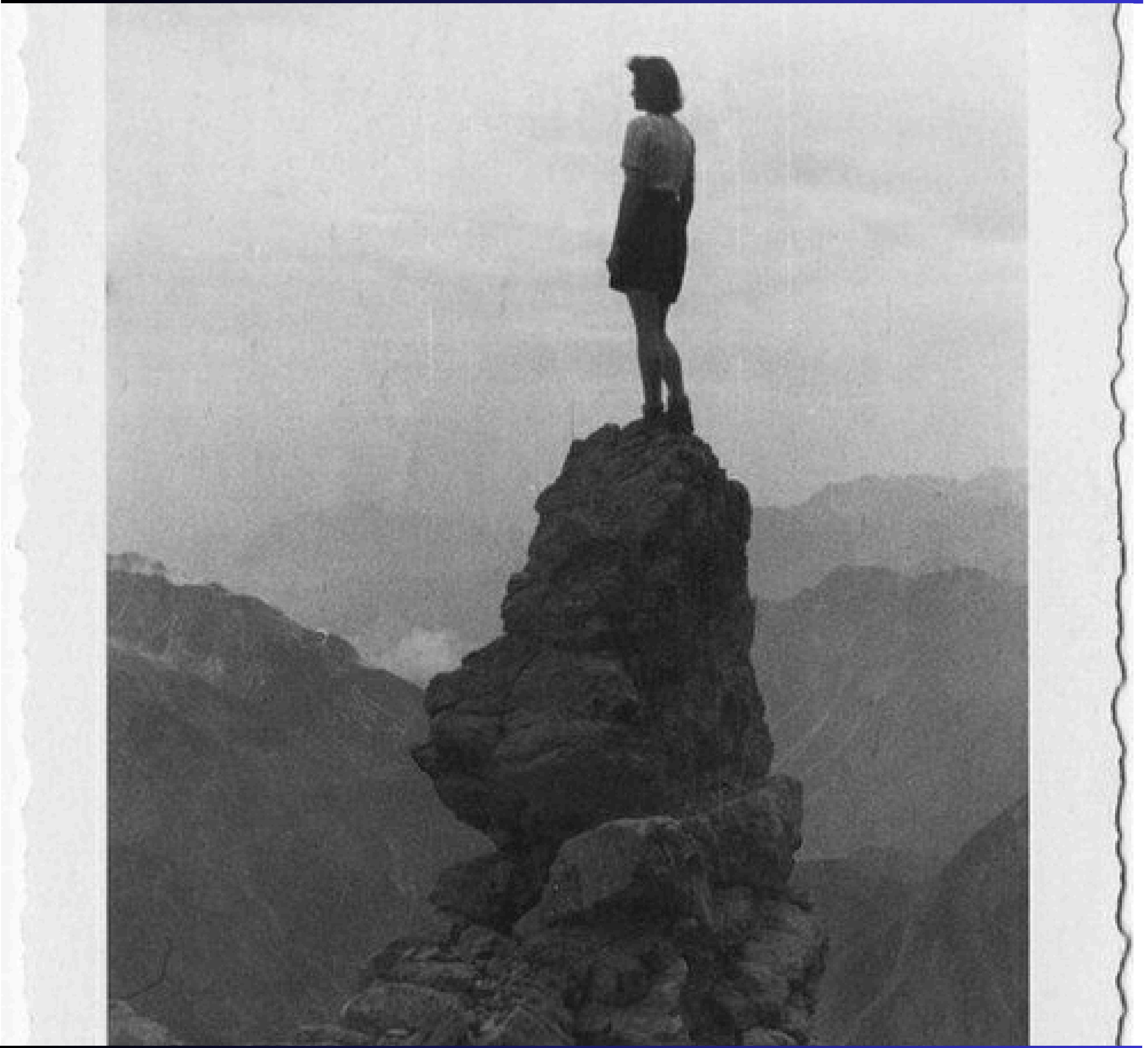
Ensemble Methods: Combine CNNs with models like Random Forests for improved accuracy.

Lower Accuracy for Temporal Data

Despite optimization efforts, RNNs show lower accuracy compared to CNNs, highlighting challenges in effectively utilizing temporal data.

Suggestion for Improving Temporal Data Accuracy:

- Try Advanced RNN Variants: Use LSTM or GRU models to better capture long-term dependencies.
- Enhance Features: Include lagged variables, seasonal indicators, or trend components.
- Optimize Hyperparameters: Adjust settings such as hidden units and learning rates.
- Consider Hybrid Models: Combine RNNs with CNNs for better feature extraction and sequence modeling.
- Increase Training Data: Provide more examples of temporal patterns to improve generalization



Results •

Effective Risk Categorization

The Random Forest model achieved 99% accuracy in classifying Düsseldorf's weather data into pleasant and unpleasant categories. Key features, "Precipitation" and "Temp Max," were identified as most influential. This high accuracy highlights the model's effectiveness in assessing weather risks and suggests strong performance in predicting extreme weather scenarios.